Intelligence by Design for The Entropic Grid

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***Abstract*—The *Smart Grid* vision has been sparked by the need for a more reliable, efficient, and sustainable energy network. However, new technologies and new policies intended to realize this vision may increase significantly the complexity of the power network. In particular, with greater consumer and supplier choice, and with the introduction of renewable energy resources that are often unpredictable, the range of possible system behaviors — that is, its *entropy* — may increase dramatically. With proper design, this entropy can be reduced, and the term 'Smart Grid' will be justified.**

A theoretical scaffolding able to deal with uncertainty and dynamics must complement the successful power and energy systems methodologies that are used today. It is necessary to have tools to understand and control complex dynamic systems subject to uncertainty, variability, and shared constraints. These tools are needed to create and evaluate new policies. We must also revisit our ways of measuring success — what do we mean by *reliability* in a system with increased user participation, and increased load shedding?

Methodology from decision & control, and simulation & learning are promising sources of techniques and results to handle uncertainty and dynamics in complex systems, taking into account the cost and reliability constraints faced in energy networks. Several techniques from these fields are surveyed in the paper.

***Index Terms*—Power system operation and planning, energy economics, smart grid, control, simulation**

I. INTRODUCTION

Many changes are coming to the power industry due to new policies and new technologies. This is bringing new challenges in operating and planning the power grid. Some of these challenges take the form of increased or more exotic dynamics, and greater volatility and uncertainty. For example, renewable energy sources will inject volatile and uncertain patterns of energy into the grid, smart meters and appliances will increase demand uncertainty, new information technologies may increase cyber-security risks, and new products and market participants may increment dynamics and uncertainty. Recent work shows that volatility and uncertainty can have tremendous impact on system operations and market outcomes [1]–[5]. New ways of thinking about both operations and long-term planning emerge as critical requirements for reliability [6]–[8].

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This paper is written with two goals in mind. First, we wish to highlight the need for new models, tools and algorithms for analysis, operation and planning of future energy systems. These tools will facilitate the design of effective market structures to achieve an economic and reliable system. Achieving this will require the effort of a multidisciplinary set of researchers from several areas such as power and energy, decision & control, economics, statistics, and even social sciences.

The second goal is to explain the need to reconsider the notion of *reliability* in energy systems. With greater reliance on demand response or load shedding, we argue that the definition of reliability should be expanded beyond today's rare-event metrics, such loss-of-load-probability (LOLP).

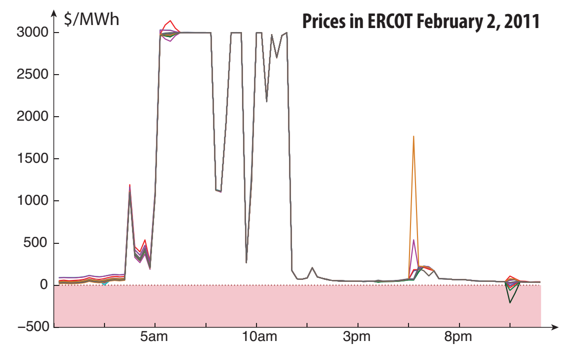

Fig. 1. Wall Street Journal, February 7, 2011, *Texas to Probe Rolling Blackouts*: Texas officials have ordered an investigation into rolling blackouts that struck the state's electric grid last week, including whether market manipulation played a role along with harsh weather in disrupting natural-gas and electricity supplies to millions of people.

How will policies change in the grid of the future? Volatility is already a significant issue in power systems policy. A very recent illustration is shown in Figure 1. Chaotic weather in Texas resulted in chaotic prices – peaking at the price cap, which is two orders of magnitude beyond the average price of power. The state government of Texas is now attempting to determine if market manipulation played a role in disrupting energy supplies in order to influence prices.

The increased dynamics, volatility and uncertainty of tomorrow's grid will increase the 'disorder' or 'uncertainty' of the system. In thermodynamics and in Shannon's theory of coding and communication, the notion of *entropy* plays a central role. In a precise sense, entropy captures the number of attainable state trajectories in a system: The larger the entropy, the larger the number of possible state trajectories on a given time-horizon. In the proposed Smart Grid, with its increased participation of consumers, and greater reliance on renewable resources, it is clear that the system will be much more 'uncertain' and it is also clear that the range of possible system behaviors may be increased greatly. For these reasons, until the appropriate level of intelligence can be assured, we adopt the term *Entropic Grid* to describe the new power grid, with all of its new complexity and uncertainty. Our intention is to highlight the fact that although new technologies and policies bring many new opportunities for a more efficient future, they also bring the potential for an extremely complex or 'entropic' system.

A basic message to the power system community is that while we recognize the potential benefits of the Smart Grid vision, we must be aware of the potential issues arising from its entropic characteristics. With proper design, this uncertainty can be reduced, and the term 'Smart Grid' will be justified.

The first step towards the design of any power grid and its associated markets is to understand the solution of the social planner's problem (SPP). The success of the system operator role in the electricity industry is explained in part by a long record of operations in a vertical way in which the realization of the SPP's solution was the key goal. The expertise and intuition of system operators, along with the infrastructure of the power grid, were developed in an evolutionary way: Over a long time horizon, with much trial and error. We believe that new technology combined with new policy will bring uncertainty and complexity that rule out the reliance on evolutionary adaptation. Our vision is that insights, techniques and methodologies from other fields such decision & control or simulation & learning can facilitate the understanding of the Entropic Grid and the transition to a Smart Grid. The goal is to obtain better intuition regarding technological and system needs for the grid of the future, and how to ensure that these needs will be met via policy combined with markets.

In this paper, we describe how techniques from decision & control, and simulation & learning can complement well-developed power systems methodologies. In the entropic grid setting, conventional static optimization based models provide a valuable *starting point* for modeling and analysis. These models must be extended to take explicitly into account dynamics, uncertainty and volatility.

Modeling and approximate optimization approaches for application in communication networks and manufacturing have been developed within the decision & control and computer science academic communities, and may lead to equally valuable tools for design and analysis in power network applications. As one example of this cross-fertilization, we provide a review of recent research concerning the role of volatility in managing reserves in electricity markets, and the nature of competitive equilibria in dynamic markets when this volatility is taken into account [3]–[5].

We hope the vision and results presented in this paper can contribute to the ongoing process of bridging the decision & control, and power and energy systems communities, reflected by several recent works on this boundary [1], [3]–[5], [9]–[15].

The remainder of the paper is organized as follows. In Section II we discuss the need to reconsider how we evaluate reliability in energy systems in a way that is appropriate in an entropic grid. We devote Section III to a discussion on the kinds of tools and models that will be needed to achieve appropriate levels of reliability. This includes a survey of recent results concerning the impact of uncertainty and volatility, in a competitive equilibrium analysis of an energy grid subject to the integration of renewable energy. Section IV presents several open questions and research directions. Finally, Section V contains concluding remarks.

II. Reliability and the Entropic Grid

Reliability of the power grid is of critical importance to our society. A recent perspective on this observation, and on new trends in risk modeling for energy systems is presented in [6]. In an entropic grid setting the well-known notion and ways to quantify reliability should be complemented with new ideas and methodologies.

The difficulty in achieving reliability *guarantees* is due in part to the breadth of meaning of the term 'reliability'. It is recognized that reliability is dependent on *time scales*: The usual time scale dependance in reliability analysis of power systems is in terms of adequacy and operational reliability, defined respectively on long- and short-time horizons. Similarly, reliability has a *locational* dimension: A black-out in the Boston area has more impact than a black-out in New Salem. In addition, reliability depends upon both the frequency and the magnitude of disruption. For these reasons, system reliability cannot be summarized in a single scalar quantity. For example, the usual procedure of planning energy systems for achieving a specific reliability target, e.g., an LOLP corresponding to 1 outage-day in 10 years, becomes hard to justify.

The need to revisit performance and reliability for the grid of the future is based on these issues and further observations:

- Consideration of operational constraints in the planning process becomes more critical. The system must be planned to withstand the increased dynamics and volatility of the entropic grid.
- We require reliability metrics that capture dynamical features of the system. For example, with sufficient *responsive or flexible* generation units we expect to obtain a more reliable system; One gigawatt from a nuclear plant is not the same as a gigawatt from a gas turbine plant, or a wind farm.
- While responsive generation and responsive demand may improve reliability, they may also lead to reliability *failure* due to catastrophic dynamics. Will delayed demand-response lead to oscillatory instability?

We believe that the several dimensions of reliability can be separated into two broad classes: The first is a measure of the frequency of *rare-events*, such as the LOLP emphasized by today's practitioners. The second is *average-cost* metrics, where the 'cost' arises from various sources, and these costs are *persistent* rather than rare.

A. Rare-event metrics

The most widely-used reliability metric in the case of electric power is based on a rare event: the "loss-of-load". The loss-of-load probability, or LOLP, is the probability that supply is not able to meet demand during a given time period. This is an important reliability criterion for system operators and planners, even with its missing elements (such as the disregard for magnitude of loss or its duration, as discussed above). In addition there is the failure to consider the topology of the transmission grid and its many constraints. However, for the LOLP or its refinements such as the presented in [8] in which a composite LOLP is introduced, the main practical issue is the computation of the probability of loss of load in a realistic large-scale power systems. This computational issue is expected to be exacerbated in an entropic grid setting in which much more uncertainty will be involved.

In the simulation research community a “rare event” is defined as expected: It is an ‘event’ such as a power-blackout that occurs rarely. Estimating the probability of a rare event can be computationally expensive, and difficult to estimate via simulation. Several tools and techniques from advanced sampling and sampling based optimization can improve the efficiency of the simulation process. However, obtaining meaningful numbers can be hard to achieve, in particular if absolute risk levels wants to be quantified [6].

B. *Average-cost metrics*

Rare-event metrics such as the LOLP are understandably an important focus of any system operator, especially because they have been around for many years. However, for all of the reasons already provided, we believe that this performance criterion must be complemented with other reliability metrics that capture persistent costs to be confronted in future energy systems. In particular, if those metrics are going to be used in cost-benefits analysis as for example in planning applications.

Two key costs that are expected to change significantly over the next decade are,

- Cost of operation of a range of generators, including both dollar amount and environmental impact
- Cost of load shedding to a range of different classes of consumers

Note that the cost of generation may actually rise with increased renewable generation because of the growing reliance on responsive generation such as gas-turbine, because of increased load shedding, or because of increased reserves [3], [4]. The impact of these costs may be very sensitive to the system structure: Is there a real time market? What percentage of the load is available for load-shedding?

C. *Reliability and Efficiency in the Entropic Grid*

We believe that the only way to address entropy is to reduce it. To achieve a reliable, predictable and more controllable system will come with cost – perhaps a loss of efficiency in the ideal sense of economics – but a necessary cost given the importance of energy in our overall economy.

This idea is not new. A clear example is highway engineering: Nobody would claim that the Los Angeles highway system is efficient. On paper we might prove that efficiency can be improved by eliminating lanes or speed limits. In practice, we know that the range of possible behavior of drivers must be reduced through lanes and speed limits to achieve a more predictable and safer transportation grid. We must accept that similar restrictions are necessary to improve predictability in the energy grid.

To begin to understand these challenges, in the following section we survey proposed models that capture volatility and dynamics of an energy grid, and we examine the predicted outcomes in the associated real-time energy markets under the most ideal assumptions of economics.

III. Tools, Models and Algorithms

Conventional static optimization based models provide a valuable *starting point* for modeling and analysis. These models must be extended to take explicitly into account dynamics, uncertainty and volatility in an increasingly entropic energy network.

We begin with a description of network models suitable for operations and analysis. We introduce a dynamic dispatch model that capture some of the dynamic issues and uncertainty of the entropic grid.

A. *Dynamic dispatch for operations*

Our models must include uncertainty in many forms. In the grid of the past, uncertainty arose from demand variability, generator outages, and weather — a factor contributing to the dramatic price volatility seen in Figure 1. Volatility will increase substantially with greater integration of energy from solar and wind sources. The uncertainty and dynamics of these energy resources are very different from anything seen in the past. In our prior work we have shown how the volatility that comes with renewable energy resources can be costly, even though these energy resources are free [4]. Greater uncertainty could be introduced with introduction of demand response, especially with dynamic, real-time pricing. While it is often argued that demand response has clear potential benefits for improving reliability and reducing overall volatility, a system with price-responsive demand may in fact be less predictable: The unconstrained behavior of consumers may reveal statistics as exotic as the wind!

Once we have settled on network architecture, the specific policy for implementing demand response, and commitment decisions for wind, nuclear, and coal generation, we will have a significant variability and uncertainty. To cope with these new dynamics combined with greater uncertainty, we will require better mechanisms for reserve management.

It is well-known that the deployment of reserves is key to hedge against such uncertainty [16]–[19]. One way to address the implementation of reserves is by applying parallels between this task, and reserve management in inventory models [1], [10]. Optimal reserves will be zonal and dynamic, depending on current loads at various zones, the mix of available generation, and the ramping capabilities of generation units.

The reserve management approaches described in [1], [10] are based on a version of the models described next.

Network topology: The basic topology is defined by a graph in which each node represents a bus, and each link represents a transmission line. A simple example is shown in Figure 2. Located at each node are one or more of the following: Generation and exogenous demand. A lossless DC model is used to characterize the relationship between generation, demand, and power on the various links. There are ℓ_n nodes, denoted $\mathcal{N} = \{1, \dots, \ell_n\}$, and L transmission lines, indexed by $\{1, 2, ..., L\}$. The network is assumed to be connected.

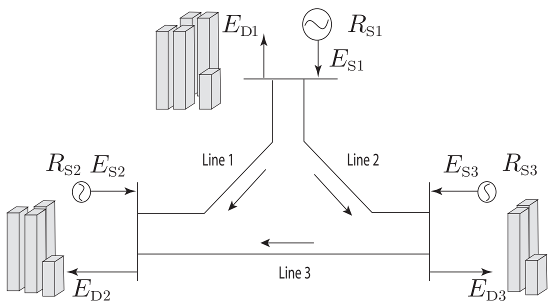

Fig. 2. Three bus system.

Demand-side: We denote by $D_n(t)$ the demand at time t, at bus n, and by $E_{Dn}(t)$ the energy withdrawn by the consumer at that bus. We assume that there is no free disposal for energy, which requires that $E_{Dn}(t) \le D_n(t)$ for all t. If sufficient generation is available at bus n at time t, then $E_{Dn}(t) = D_n(t)$. In the event of insufficient generation, we have $E_{Dn}(t) < D_n(t)$, i.e., the consumer experiences a blackout.

Supply-side: We denote by $E_{Sn}(t)$ and $R_{Sn}(t)$ the energy and reserve produced by the supplier at bus n. Generation capacity, $\boldsymbol{G}_S$, coincides with $\boldsymbol{E}_S + \boldsymbol{R}_S$. The operational and physical constraints on the production of energy and reserve are expressed abstractly as

$$(\boldsymbol{E}_S, \boldsymbol{R}_S) \in \mathsf{X}_S \tag{III.1}$$

The usual DC power flow relations are included for the transmission system. In addition, rate constraints are imposed on generation that are a consequence of the physics of both generators and the grid.

Constraints: The remaining assumptions on the dynamic network model are described as follows:

(i) Generation capacities are subject to strict bounds: For $n \in \mathcal{N}$ and $t \ge 0$,

$$G_n(t) \le \overline{G}_n \tag{III.2}$$

where $\overline{G} = (\overline{G}_1, \dots, \overline{G}_{\ell_n})^T$ are fixed ℓ_n-dimensional vectors.

(ii) Generation capacity is *rate constrained*: For all $t_1 > t_0 \ge 0$,

$$\zeta^- \le \frac{E_S(t_1) - E_S(t_0)}{t_1 - t_0} + \frac{R_S(t_1) - R_S(t_0)}{t_1 - t_0} \le \zeta^+ . \tag{III.3}$$

(iii) Lossless network, so it neither generates nor consumes energy. Consequently, the network is subject to the supply-demand balance constraint,

$$1^T E_S(t) = 1^T E_D(t)\,, \quad t \ge 0 \tag{III.4}$$

(iv) Power flows over the network are consistent with the DC power flow model. Suppose bus 1 is selected as the reference bus, based on which the *injection shift factor matrix* $H \in [-1, 1]^{N \times L}$ is defined, where H_{nl} denote the power distributed on line l when 1 MW is injected into bus n and withdrawn at the reference bus [1].

Let $f_l^{\max}$ denote the capacity of transmission line l. On letting $H_l \in \mathbb{R}^N$ denote the l-th column of H, the capacity constraint for line l is expressed,

$$-f_l^{\max} \le (E_S - E_D)^T H_l \le f_l^{\max} \tag{III.5}$$

The network shown in Figure 2 provides an example of the general model in which there are sources of demand and supply at each of three nodes.

The vector of nodal power flows P is given by,

$$P = (E_{S1} - E_{D1}, E_{S2} - E_{D2}, E_{S3} - E_{D3})^T ,$$

where the directions of positive power flows are as indicated by arrows in the figure. If the impedances are identical in the three transmission lines, then with bus 1 chosen as the reference bus, the injection shift factor matrix is given by

$$H = \frac{1}{3} \begin{bmatrix} 0 & 0 & 0 \\ -2 & 1 & -1 \\ -1 & -1 & -2 \end{bmatrix} \tag{III.6}$$

The flow on the lines are given by $P^T H$.

B. The Social Planner's Problem

Based on this model we can make precise the optimization goals posed by the social planner. This is the first step in assessing the efficiency of an outcome in a market setting.

Objective Function: To formulate a control problem we introduce a cost function. The production cost for energy injected at bus n at time t is denoted $c_n^E(E_{Sn}(t))$, and for the reserve provided at that bus is $c_n^R(R_{Sn}(t))$. The marginal cost of black-out is denoted c_n^{bo}. For given generation, reserves, and demand $\{E_{Sn}, R_{Sn}, D_n, E_{Dn}\} \subset \mathbb{R}^{\ell_n}$, the cost function $c(E_{Sn}, R_{Sn}, D_n, E_{Dn})$ is defined by,

$$\sum_{n \in \mathcal{N}} \big(c_n^E(E_{Sn}) + c_n^R(R_{Sn}) + c_n^{bo}(D_n - E_{Dn})_+ \big). \tag{III.7}$$

Optimization problem: Putting all the above elements together, the basic optimal control problem becomes,

$$\min_{\boldsymbol{E}_D, \boldsymbol{E}_S, \boldsymbol{R}_S} \int_0^\infty e^{-\eta s} \mathsf{E}_x[c(s)]\, ds, \tag{III.8}$$

subject to the operational/physical constraint (III.1), the network constraint (III.5), and energy-balance constraint (III.4). The optimization problem (III.8) is a sort of *dynamic economic dispatch*, in which the objective function corresponds to the expected discounted total cost.

Observe that the cost is a function of the $4\ell_n$ variables contained in the ℓ_n-dimensional vectors $\{E_{Sn}, R_{Sn}, D_n, E_{Dn}\}$. For a network with 1000 generators in operation, such as the California system, this model is not suitable for mathematical analysis. Techniques from decision and control such as aggregate models and workload relaxations lead to a tractable model that can be approximately solved. For example, in [1] insights about effective reserves policies for a similar model are obtained.

This dynamic extension of the usual economic dispatch model is used as the starting point for analyzing the competitive equilibria and the impact of volatility in electricity markets. Topics of the next two sections.

C. Dynamic competitive equilibrium for dynamics markets

The competitive equilibrium is an idealization in which it is assumed that no market player is large enough to influence prices. In typical analyses of static market models, the prices in this equilibrium are equal to the marginal cost of production. In our prior work we find that this holds only on average [2]–[4]. The sample path behavior of prices can look as erratic as the worst days during the crises in Illinois or California in the 1990s, or in Australia today.

To explain these conclusions we recall the Lagrangian decomposition analysis in our recent work [3]. The consumer and supplier's objective function is the long-run discounted expected profit with discount rate γ, represented by

$$K_{\text{D}} := \mathsf{E}\Big[\int e^{-\gamma t}\mathcal{W}_{\text{D}}(t)\,dt\Big]\,,\quad K_{\text{S}} := \mathsf{E}\Big[\int e^{-\gamma t}\mathcal{W}_{\text{S}}(t)\,dt\Big]$$

The supplier and consumer each aim to maximize their respective mean discounted mean welfare K_{S}, K_{D}. We let $\mathcal{W}(t) := \mathcal{W}_{\text{S}}(t) + \mathcal{W}_{\text{S}}(t)$ denote the welfare function of the social planner.

The form of the welfare functions $\{\mathcal{W}_{\text{D}}(t), \mathcal{W}_{\text{S}}(t)\}$ is not important for our purposes here — The only requirement is that the sum be equivalent to the negative of the cost $c(t)$ defined above (III.8): For some constant κ,

$$\mathsf{E}[\mathcal{W}(t)] = \kappa - \mathsf{E}[c(t)], \qquad t \ge 0.$$

We now impose several idealistic assumptions for this dynamic model, each of which is an extension of what is assumed in the competitive equilibrium analysis of a static model.

(i) Consumers and suppliers share equal information. This is modeled as a *filtration*: An increasing family of σ-algebras, denoted $\mathcal{H} = \{\mathcal{H}_t : t \ge 0\}$. The demand process, and the decisions of the consumers and the suppliers are adapted to this filtration.

(ii) There is a price process $\boldsymbol{P}^e$ that is adapted to $\{\mathcal{H}_t : t \ge 0\}$. However, prices are *exogenous*: For each $t_0 > 0$, the future prices $\{P^e(t) : t > t_0\}$ are conditionally independent of $\{E_{\text{D}}(t), E_{\text{S}}(t) : t \le t_0\}$, given current and past prices $\{P^e(t) : t \le t_0\}$.

Assumption (ii) is known as the *price-taking assumption* [20].

To Lagrangian decomposition of [3] is obtained on relaxing the constraint that $E_{\text{D}}(t) = E_{\text{S}}(t)$ for all t. Let $\{\lambda(t)\}$ denote a vector-valued stochastic process that is adapted to $\mathcal{H}$, of the same dimension as $E_{\text{D}}(t)$ or $E_{\text{S}}(t)$, and consider the Lagrangian relaxation: The dual functional $\Phi(\lambda)$ is defined as the supremum of,

$$\mathsf{E}\Big[\int e^{-\gamma t}\big(\mathcal{W}(t) + \lambda(t)^{\scriptscriptstyle T}(E_{\text{D}}(t) - E_{\text{S}}(t))\big)\,dt\Big]$$

over all adapted processes $\boldsymbol{E}_{\text{S}}$, $\boldsymbol{E}_{\text{D}}$. Under the assumptions of our prior work, this optimization problem is decomposed into two problems — one for the consumer, and one for the supplier, as follows:

$$\begin{aligned}\Phi(\lambda) = \max_{\boldsymbol{E}_{\text{D}}} \mathsf{E}\Big[\int e^{-\gamma t}\big(\mathcal{W}_{\text{D}}(t) + \lambda(t)^{\scriptscriptstyle T} E_{\text{D}}(t)\big)\,dt\Big] \\ + \max_{\boldsymbol{E}_{\text{S}}} \mathsf{E}\Big[\int e^{-\gamma t}\big(\mathcal{W}_{\text{S}}(t) - \lambda(t)^{\scriptscriptstyle T} E_{\text{S}}(t)\big)\,dt\Big]\end{aligned} \tag{III.9}$$

Under general conditions there is no duality gap: There is a process $\boldsymbol{\lambda}^*$ for which the solutions to (III.9) and the social planner's problem (III.8) coincide. Moreover, by inspection it follows that this forms a solution to the competitive equilibrium, with $P^e(t) = \lambda^*(t)$ for each t.

Because of unique features of a power market, the equilibrium price process looks very different from the solution obtain for a static model:

(i) The price is marginal value to the consumer. In particular, when reserves are positive at a node in the network, the price is *zero*.

(ii) In the market models of [2] or [3], the average price for power is never less than the average marginal cost: For each node n,

$$\mathsf{E}\Big[\int e^{-\gamma t}P^e_n(t)\,dt\Big] \ \ge \mathsf{E}\Big[\int e^{-\gamma t}\big(\frac{d}{de}c^{\text{E}}_n\,(E_{\text{S}n}(t))\big)\,dt\Big]$$

Equality holds under mild conditions.

(iii) If the variance of demand or supply is large, then the variance of $\boldsymbol{P}^e$ will also be large.

Note that all of our discussion has focused on optimization in the real-time market (RTM). In practiced, this is coupled with a day-ahead market (DAM) in which generation is scheduled to meet expected energy requirements, as well as reserves. A model designed to couple the two markets is proposed in [4], in which the welfare functions for both suppliers and consumers are extended to include 'day-ahead' welfares,

$$\mathcal{W}^{\text{tot}}_{\text{D}}(t) = \mathcal{W}_{\text{D}}(t) + \mathcal{W}^{\text{da}}_{\text{D}}(t)\,,\quad \mathcal{W}^{\text{tot}}_{\text{S}}(t) = \mathcal{W}_{\text{S}}(t) + \mathcal{W}^{\text{da}}_{\text{S}}(t) \tag{III.10}$$

The details of this construction can be found in the paper. In the following section we survey the market implications of our analysis.

The results surveyed in this section can be interpreted in various ways. First, we have shown that prices are highly volatile even in the most idealistic assumptions of the competitive free-market, so that prices as shown in Figure 1 should not be surprising. On the other hand, under general conditions, in this equilibrium the average price of power is only the average marginal cost of generation [2], [3]. Given the high variance of prices, we wonder how the suppliers can stay in business? We wonder if there would be any incentive to enter the real-time market? We can come to completely different conclusions on re-examining our assumptions: The results of this section are all based on the assumptions of competitive equilibrium theory — we believe that these provide only a crude model of reality in power systems applications. *Information is not symmetric*: The consumers do not have access to the same information as the suppliers. *Prices are not exogenous*: The number of suppliers is finite, so there is ample opportunity to exercise market power to influence prices in a real-world setting. Are the prices shown in Figure 1 the result of market power, or the natural price fluctuations in a competitive equilibrium? We don't know, because we don't know what the generator operators are thinking.

This brings us to a source of uncertainty that is potentially greater than the wind: The behavior of the consumers and suppliers of electricity. We cannot pretend to know exactly how the suppliers and consumers will behave to further their interests. This fact brings many research challenges — We provide some examples in Section III-D.

D. The value of volatile resources in electricity markets

There are well-known environmental, economic and common good reasons for having a cleaner energy mix. Wind power is currently one of the more deployed renewable energy sources due to reduced investment costs, short installation time, and little operational costs [21]. However, the limited control capabilities of wind generation along with the inherent intermittency and uncertainty create a challenging environment for system and markets operators. From an operational viewpoint, it requires changing procedures such reserve management to ensure the reliability of the grid. From a market viewpoint, it entail the need to rethink market designs created for a less uncertain, volatile and dynamic setting to ensure appropriate features of the market outcomes.

In [4] we evaluate the impact of volatile resources by focusing in two parameters: penetration and volatility of wind. We present the main ideas and results here — further details can be found in the paper.

The model is a coupling of real-time and day-ahead markets, in which the day-ahead market (DAM) is modeled with the usual features: one day before the real operation of the real-time market, the DAM is cleared and generation is scheduled to meet the expected demand and reserves requirements.

We adopt the usual policy of '*dispatching all the wind*'. We model the resulting market by interpreting wind generation as a negative load. The resulting residual demand is denoted by $D^{\text{net}}(t) = D(t) - G_{\text{w}}(t)$ and we obtain expressions for consumer and supplier welfare with respect to residual demand.

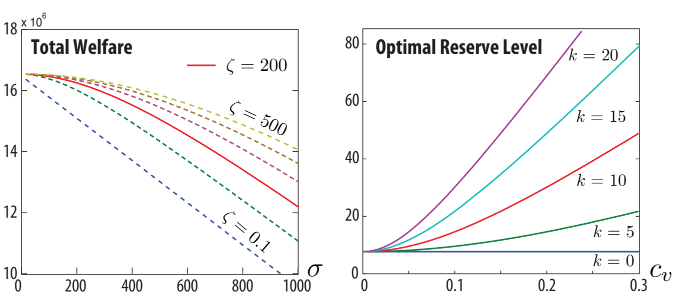

Fig. 3. Social planner's welfare and optimal reserves.

The welfare function of the social planner is the sum $\mathcal{W}_{\text{D}}^{\text{tot}}$ defined in (III.10). We have stated that in [4] we focus on two parameters: penetration and volatility of wind. In our numerical studies, the wind variance is denoted σ_{w}^2, and the wind resource penetration is $\mathsf{E}[G_{\text{w}}(t)]$. The coefficient of variation of wind and the percentage of wind resource penetration are denoted, respectively, by

$$c_v := \frac{\sigma_{\text{w}}}{\mathsf{E}[G_{\text{w}}(t)]} \quad \text{and} \quad k = 100\frac{\mathsf{E}[G_{\text{w}}(t)]}{\mathsf{E}[D]} \tag{III.11}$$

Figure 3 shows the optimal mean social welfare under the assumptions of [4]. As expected, the welfare decays rapidly with decreased ramping rate ζ or increased volatility.

Next we consider the competitive equilibrium of [3]–[5] for this model. The prices in this equilibrium result in an efficient outcome. Although their sample-path behavior may be as exotic as those seen in Figure 1, under general conditions, the average price is only the average marginal cost.

We provide the mean welfare of the consumers and suppliers in the competitive equilibrium in one special case: We assume that the consumers command all wind generation resources. In this case, consumers do not have to pay explicitly by wind power — the impact is just a modification of the consumer's load. However, as we will see, large wind volatility can result in welfare losses for consumers even when the wind energy comes without cost. This is explained by the results shown in Figure 3: The optimal reserve level increases with wind penetration or wind volatility. The additional cost to the consumer is the cost of maintaining additional generation reserves, just in case the wind patterns change suddenly.

This additional cost is illustrated explicitly in Figure 4, showing the actual values of the mean consumer and supplier welfare. When wind volatility is low, the consumer benefits from greater wind penetration. This is not surprising since wind is assumed to be 'free' to the consumer in this calculation. This conclusion can be arrived at as the result of typical static-based analyses for wind power. However, the situation changes dramatically with increasing volatility. When the variance exceeds a certain level, consumers are better off not using all available wind generation. In contrast, suppliers benefit from higher volatility.

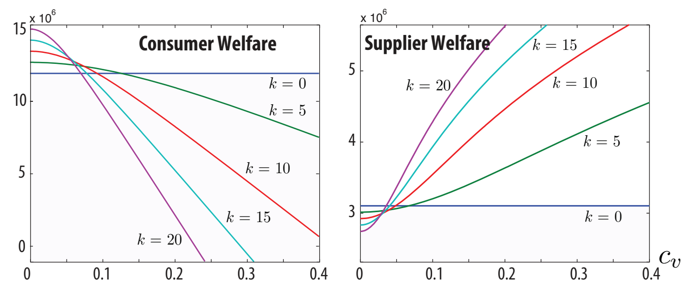

Fig. 4. Consumer and supplier welfare: consumers command wind.

These results underline a primary research agenda for managing the entropic grid: How to handle the impact of volatility and uncertainty injected by suppliers of energy from volatile resources such as wind (especially in a market setting)? This will require the deployment of demand- and supply-side management procedures, as well as new market structures.

IV. Open Questions and Research Frontiers

Current electricity markets have emerged from the evolution of a vertically integrated, centrally planned system, to the regulated markets seen around the world today. The entropic grid with its increased level of uncertainty and dynamics will require new ways to think about system planning, operations, and markets.

A. Cross-disciplinary research

The transition from the Entropic Grid to the Smart Grid will require collaborations among researchers from disciplines such as power, control engineering, applied mathematics and social sciences. Within the fields of decision & control there are model reduction techniques that may prove valuable, such as the 'workload relaxation' approach to model reduction of stochastic networks [1], [10]. Optimization for complex stochastic models will likely draw from recent techniques in simulation & learning, including particle filters and machine-learning techniques used for approximate dynamic programming. We hope that our own research in these areas, such as the techniques developed in [22]–[26], will help solve planning and operation problems in the entropic grid, such as the management of supply, storage, and demand.

B. Beyond usual economics

It is clear that market structures must change to meet the challenges surveyed in this paper. It is necessary to complement static-based economic models with dynamic models that take into account uncertainty. At the same time, we must recognize that the non-linearities, uncertainties and irrational behavior of the real world mean that the predictions from our idealized models will sometimes fail. To achieve a reliable system we must take into account a range of issues – reliability, environmental, safety – along with the usual notion of economic efficiency.

In the competitive equilibrium setting, once dynamics and uncertainty are brought into play, the competitive outcome of real-time markets are characterized by volatile and high prices. Advocates of the current RTM paradigm may argue that there is no problem: If this is what the competitive equilibrium looks like, then we better accept volatile prices and prices spikes because in the 'long-term' society will be better. We counter: Is it really so important that we achieve this 'long-term' or 'equilibrium' nirvana in the energy grid? How can we be so sure that we will converge? Moreover, recall that in the competitive equilibrium described in Section III-C, the variance of income to suppliers is high, while the average price coincides with the average marginal cost. This creates significant barriers to entry, and lowers the incentive to remain in the RTM.

While the competitive equilibrium analysis may give some insight, it is a crude model of reality, and in particular far too crude for long-term predictions of system behavior. Energy companies are seeking profits: Big profits may come from 'disruptive technologies', or from 'market manipulation'. By the time we converge to the hypothesized optimal equilibrium, the entire system would have changed due to new policies and new technologies. Consequently, we believe the notion of 'long-term' convergence is meaningless in energy markets.

The energy grid is as important to our society as our transportation systems or healthcare systems. Reliability of the grid is critical — blackouts can have tremendous social and economic costs, wasting all the 'efficiency' improvements and gains of several years. The best architecture for the energy highway of the future is not yet obvious to us, but it is likely to include elements of todays DAM combined with long-term contracts. However, it is obvious that we will need lanes and speed limits, incentives and penalties, in order to achieve a reliable system.

V. Concluding Remarks

We have argued that an Entropic Grid may emerge as a result of many of the proposed Smart Grid initiatives, and that traditional reliability metrics must be updated in view of the greater uncertainty in the entropic grid. The LOLP criterion will remain important, but we must also include cost-based metrics for reliability.

Many of the issues surveyed in this paper will require the application of successful power and energy methodologies of the past, complemented with approaches from other disciplines such as decision and control, and simulation and learning. In particular, we need a wider range of tools to address dynamics and volatility.

We strongly believe that a new paradigm for the design and operation of future energy markets is required. We must move beyond traditional static competitive equilibrium analysis. It is essential that we take into account not only economic efficiency, but objectives such as sustainability and reliability.

We believe that the issues surveyed in this paper reveal many exciting open research frontiers. We hope that this research will move us towards a new paradigm for design of energy systems and their markets.

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